REMARKS

I. Request for Information, 37 CFR § 1.105

In the Office Action dated May 22, 2007, the Examiner requested that in accordance with CFR § 1.105, the Applicant provide detailed test data, appropriate written description of the meaning of such test data including pictures of test setup to demonstrate that the claimed invention has been reduced to practice.

Applicant's invention relates to nanoconnections that are grown directly within the gap rather than at the electrodes. In order to demonstrate this feature of Applicant's invention and ultimately, Applicant's overall nanometer scale based device, consider the case of a charged nanoparticle suspended in a liquid dielectric solution between two electrodes. Applicant presents the following discussion to demonstrate that the nanoconnections formed in a solution and attracted to a connection gap (rather than electrodes) is based on practical principals and can function as a neural network. (Note: Applicant is, of course, not asserting that his nanoparticles must be charged, but just providing a helpful illustration). Consider that an <u>alternating</u> electric field is applied across the electrodes. Because the field is alternating, the charged particle is equally attracted and repelled to/from both electrodes. Nanoparticles are moved by a dipole induced force, e.g., the dielectrophoretic force. Such a force can be described mathematically as follows:

$$\vec{F}_{dep} = 2\pi r^3 \varepsilon_0 \varepsilon_m \, \mathrm{Re}\left[\frac{\varepsilon_p^* - \varepsilon_m^*}{\varepsilon_p^* + 2\varepsilon_m^*}\right]\nabla E^2$$

Note that the force is dependent on the <u>gradient</u> of the <u>square of the magnitude of the electric field</u>. It is standard physics knowledge that the electric field inside a conductor is zero. As soon as a conducting nanoparticle touches an electrode there can be no electric field between the nanoparticle and the electrode

because their electric potentials are equal. Thus, the moment the particle actually touches the electrode is the moment the dielectrophoretic force is in essence turned off. One can then argue that the particle was in fact attracted to the electrode gap and not the electrode.

In order to demonstrate these concepts, the Applicant refers to the following document, Hong et al. (which is included herewith). A figure from the Hong et al reference is shown below for the convenience of the Examiner:
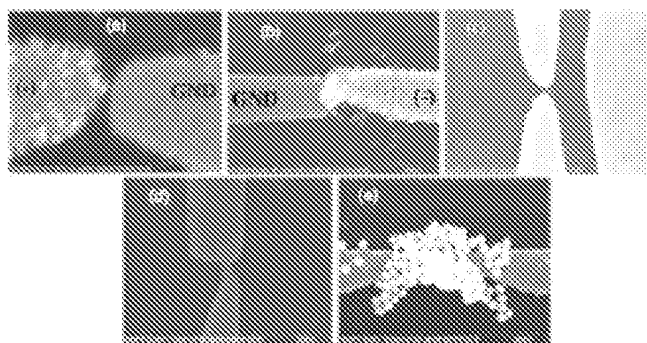

Fig. 2. (a) SEM image of captured Au nano-particles of diameter 20 nm under DC bias of - 2.05 V. (b) SEM image of captured Au nano-particles of diameter 40 nm under DC bias of - 3.3 V. (c) SEM image of captured Au nano-particles of diameter of 20 nm under AC bias of 1 V (peak-to-peak), 100 kHz, for 8 seconds. (d) SEM image of captured Au nano-particles of diameter 30 nm under AC bias of 4 V, 1 MHz for 40 seconds. (e) SEM image of captured Au nano-particles of diameter 50 nm under AC bias of 5 V, 1 MHz, for 300 seconds.

The Hong et al reference, which post dates this patent application, demonstrates that particles are attracted only to the electrode gap. One needs only compare Fig. 2(b) to Fig. 2(d) of the Hong et al reference. In Fig. 2(b) a non-alternating (i.e., static) voltage is applied across electrode terminals. Because the gold nanoparticles obtain a net positive charge when placed in solution, they are attracted only to the negative electrode. Contrast this with the case shown by Fig.

2(d) of the Hong et al reference where the applied voltage is now alternating. Note how the particles are only attracted to the electrode gap and do not accumulate on either electrode. Fig. 2(e) shows what happens when the magnitude of the alternating voltage is increased by a volt and allowed to continue for 260 seconds longer. Note that the accumulation of particles is directed to the electrode gap. However, the abundance of particles requires that they necessarily touch the electrodes. It is very clear by these pictures that particles are attracted to the gap and not the electrodes themselves. The Hong reference does not use "colloidal chains" such as those discussed by the Examiner in the May 22, 2007. The use of colloidal chains and electroheological fluids is something completely different.

The Applicant respectfully encourages the Examiner to explore the field of negative dielectrophoresis whereby certain electrode geometries can be used to trap non-charged particles while never touching the electrodes. The Applicant also encourages the Examiner to explore the area of laser tweezers because both of these fields directly manipulate charge neutral particles without ever touching them with electrodes.

The Applicant submits that the submission of the Hong reference (which is not prior art, because it does not pre-date Applicant's invention) satisfies the Examiner's request for information under 37 CFR 1.105 in that the Hong reference shows that nanoconnections can be formed when subject to a dielectrophoretic force and are not formed in chain formations and/or in electroheological fluids or colloidal suspensions, but are instead attracted to a connection gap rather (rather than electrodes).

The Applicant additionally cites MPEP 2138.05 as follows:

2138.05 "Reduction to Practice" [R-5] - 2100 Patentability

Reduction to practice may be an actual reduction or a constructive reduction to practice which occurs when a patent application on the claimed invention is filed. The filing of a patent application serves as conception and constructive reduction to practice of the subject matter described in the application. Thus the inventor need not provide evidence of either conception or actual reduction to practice when

relying on the content of the patent application. *Hyatt v. Boone*, 146 F.3d 1348, 1352, 47 USPQ2d 1128, 1130 (Fed. Cir. 1998).

Thus, the filing of Applicant's patent application is evidence of a reduction to practice, being a constructive reduction to practice. However, the Hong reference cited herein and included with this response provides evidence that nanoconnections can be formed in a solution and attracted to a connection gap (rather than electrodes) to form such connections.

Additional evidence of an actual physical neural network is disclosed in U.S. Patent No. 6,889,216, which issued to the Applicant on May 3, 2005. For the convenience of the Examiner, U.S. Patent No. 6,889,216 is also included herewith. The Applicant submits that the combination of the Hong reference and U.S. Patent No. 6,889,216 provides evidence of a physical neural network consistent with Applicant's claimed invention.

Applicant submits that the foregoing satisfies the reply required under 37 CFR 1.105.

II. Prior Art Anticipation

In the Office Action dated May 22, 2007, the Examiner provided a discussion of "Prior Art Anticipation". The Examiner, however, did not indicate under which specific section of 35 U.S.C 102 (a, b, c, d, etc?) this discussion relates. The Examiner argued that Applicant's concept of a liquid dielectric solution comprising a mixture of a plurality of nanoconductors and a liquid dielectric solvent wherein a plurality of nanoconductors are free to move about in a dielectric solution and such solution is disposed between two electrodes is anticipated by Paul M. Adriani and Alice P. Gast in the article entitled "Electric-field-induced aggregation in dilute colloidal suspensions" (hereinafter referred to as Adriani) published in 1990 by the Faraday Discussions of the Chemical Society. The abstract is cited as follows:

> Electric-field-induced chain formation in dilute, non-aqueous suspensions of sterically stabilized, 1 µm poly (methyl methacrylate) (PMMMA) lattices are investigated. Optical

microscopy and digital image analysis provide the chain-length distribution. We find that the particles carry a charge sufficient to inhibit field-induced aggregation. Equilibrium predictions of chain aggregation incorporating a screened Coulombic repulsion and field-induced dipole attraction agree with experimental observations near the onset of aggregation; chain formation becomes diffusion limited above the threshold field strength.

The Applicant respectfully disagrees with this assessment. The abstract and reference cited by the Examiner relates to the formation of "chains" in non-aqueous suspensions. Applicant is not developing electric-field induced <u>chain</u> formations. A "chain" implies direct connections between the <u>colloidal</u> particles as described in the Adriani paper. A chain is a series of things depending on each other as if linked together. Applicant's invention, on the other hand, relates to an <u>adaptive synaptic element</u> comprising a plurality of <u>nanoconductors</u> <u>suspended and free to move</u> about in a liquid dielectric solution located within a connection gap formed between at least one pre-synaptic electrode and at least one post-synaptic electrode. Thus, Applicant's invention does not rely on the use of a "chain" but is instead composed of nanoconductors that are suspended and free to move in the dielectric solution and not subject to a chain formation as is the case with the Adriani reference. Additionally, Adriani teaches the use of electroheological fluids, which are not dielectric solutions. Additionally, there is no teaching in Adriani of any type of a neural network or neural network components such as synapses. Also, Applicant's invention does not rely up on colloidal suspensions. In fact, the use of a colloidal suspension would be detrimental to the workings of Applicant's invention due to the fact that colloidal particles in colloidal suspensions are typically not on the nanometer scale.

The Examiner further asserted that Related to terminology, Applicant has not defined the term Nanotechnology. The Examiner cites From the web @ www.answers.com/nanotechnology, the following definition: Nanotechnology: the science and technology of building devices, such as electronic circuits, from single atoms and molecules.

The Examiner referred to the Nanotechnology web site created by Dr. Ralph Merkle, the statement is made that the "word nanotechnology has become very popular and is used to describe many types of research where characteristic dimensions are less than about 1,000 nanometers" (micron range). http:www.zyvex.com.nano/.

The Examiner argued that the Applicant has not defined "nanotechnology" related to a specific numeric scale. The Examiner cited Applicant's specification regarding size comparison @ specification, page 6, lines 15-18:

> Microelectrical nano-size components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro -sensors, micro-actuators, microinstruments, micro-optics, and the like.

The Examiner argued that the Applicant indicated that such definition is entirely consistent with the above cited definitions/intent.

The Applicant respectfully disagrees with this assessment. The Applicant has defined "nanotechnology" related to a specific scale. See Paragraph [0016] of Applicant's specification, which indicates the following:

> The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage.

Thus nanotechnology is something that must be at least on the nanometer scale. Adriani is not a nanotechnology reference as there is no teaching of "nanometer-scale" components and devices. In fact, Page 23, Paragraph 5, Lines 1-2 of Paragraph 5, of the Adriani reference specification indicates the following dimensions:

> "We measure suspension conductivity...in a stainless steel Couette cell of a 13 mm cylinder with a 12 mm radius and a gap of ca. 0.5 mm"

This is not a nanometer-scale device. Instead these dimensions (millimeters) are much larger. Thus, Adriani is not a nanotechnology-based device. For these reasons (e.g., Adriani is not nanotechnology, electroheological fluids are not

dielectric in nature, no teaching or hint in Adriani of neural networks, synapses, etc), Adriani does not anticipate Applicant's invention.

The Examiner further stated that related to terminology, Applicant refers to a solvent in the generic sense in the specification, page 25, ¶ 0099, that includes a condition of suspension.

Related to terminology, the Examiner also asserted that the Applicant refers to a liquid dielectric solution without any explicit definition of dielectric. The Examiner argued that dielectric means, to one of ordinary skill in the art, a non-conducting or insulating substance which resists passage of electric current, allowing electrostatic induction to act across it. The Examiner argued that a liquid dielectric solution will inherently have an electric conductance that is less than that when the subject solution has conducting material suspended in it such as the claimed nanoconductors.

The Applicant cited Adriani, the following on page 20, line 1:

Particles having aligned dipoles will aggregate into chains.

The Applicant again submits that the use of dipoles aggregated into chains is not a feature of Applicant's invention and in fact would not function in the context of Applicant's invention, because Applicant's nanometer scale nanoconductors do not form chains or links as is the case with the Adriani reference. Instead, Applicant's invention provides for nanometer scale nanoconductors that are disposed and free to move about in the dielectric solution, not chained to one another, even after application of an electric field.

The Examiner further argued that Mehrotra et al. in Elements of Artificial Neural Networks cites the nature of neural networks to include a feed forward neural network in Figure 1.15 on page 20; the adaptive linear element of Figure 2.8 with weight adjustments into a summation circuit with a training algorithm identified in Figure 2.9 on page 59. The Examiner asserted that Mehrotra, among others, assert neural networks with layers of nodes feeding with a plurality of

connections into a plurality of nodes at the next layer. Applicant notes that Mehrotra provides no teaching whatsoever of nanotechnology based devices. In fact Mehrotra provides only for a teaching of software-based neural network solutions, not actual physical artificial neural networks. For example, page 46, section 2.3 of Mehrotra provides for a detailed discussion of a "perceptron training algorithm". An algorithm is not "physical" but is instead a mathematical and hence software construct. One skilled in the art would not look to Mehrotra for a teaching of a nanometer-scale physical neural network device. Mehrotra is simply one of many references dealing with software-based neural network solutions. Applicant's solution overcomes the problems with software/algorithm neural networks. There is a discussion of software-based problems in Applicant's specification so there is no need to repeat that here.

One of the points of Applicant's invention is that most prior art neural networks are software-based and have inherent limitations. Applicant's background section points out that neural networks that have been developed to date are largely software-based. A true neural network (e.g., the human brain) is massively parallel (and therefore very fast computationally) and very adaptable. For example, half of a human brain can suffer a lesion early in its development and not seriously affect its performance. Software simulations are slow because during the learning phase a standard computer must serially calculate connection strengths. When the networks get larger (and therefore more powerful and useful), the computational time becomes enormous.

For example, networks with 10,000 connections can easily overwhelm a computer. In comparison, the human brain has about 100 billion neurons, each of which can be connected to about 5,000 other neurons. On the other hand, if a network is trained to perform a specific task, perhaps taking many days or months to train, the final useful result can be built or "downloaded" onto a piece of hardware and also mass-produced. Because most problems requiring complex

pattern recognition are highly specific, networks are task-specific. Thus, users usually provide their own, task-specific training data.

A number of software simulations of neural networks have been developed. The Mehrotra reference is but one of many prior art software (algorithm) based neural networks. Because software simulations are performed on conventional sequential computers, however, they do not take advantage of the inherent parallelism of neural network architectures. Consequently, they are relatively slow. One frequently used measurement of the speed of a neural network processor is the number of interconnections it can perform per second.

For example, the fastest software simulations available can perform up to approximately 18 million interconnects per second. Such speeds, however, currently require expensive super computers to achieve. Even so, approximately 18 million interconnects per second is still too slow to perform many classes of pattern classification tasks in real time. These include radar target classifications, sonar target classification, automatic speaker identification, automatic speech recognition, electro-cardiogram analysis, etc.

The implementation of neural network systems has lagged somewhat behind their theoretical potential due to the difficulties in building neural network hardware. This is primarily because of the large numbers of neurons and weighted connections required. The emulation of even of the simplest biological nervous systems would require neurons and connections numbering in the millions and/or billions. Due to the difficulties in constructing such highly interconnected processors, currently available neural network hardware systems have not approached this level of complexity.

Mehrotra is limited to the teaching of a software-based neural network system and algorithms thereof, and there is also no hint, teaching or suggestion of nanotechnology, let alone neural networks based on nanotechnology.

The Examiner also referred to Therese C. Jordan et al. writing in 1989 in the IEEE, Entitled "Electrorheology" in order to cite a graphic illustration of dipole

arrangement in the presence of an electric field in figure 16. on page 867 which was copied from an article published in 1978 by H>A> Pohl, entitled: Dielectrophoresis: The behavior of neural matter in nonuniform fields. The Examiner argued that arrangements follow dipole to dipole aligned to the field between the electrodes. The Examiner also argued that there is no evidence of dipoles forming nodes and dipoles crossing from one chain to other chains as is required in the formation of neural networks. (Note: Applicant does not form chains). The Examiner also argued that, in the cited Coulombic repulsion, such repulsion will prevent extension of dipoles. (Note: Applicant does not use Coulombic repulsion) The Examiner further argued that there is no formation of chains to form weights to adjust values at a given node. (Note: Again, Applicant does not form chains). The Applicant notes that such arguments do not make sense in light of the Hong reference, particularly given the field of electrorheology is completely different from that of the field taught by Applicant's invention and is in fact irrelevant with respect to Applicant's invention. The Applicant invites the Examiner to review the Hong reference, which does not teach "chains" or Coulombic repulsion, but instead shows nanoconnections attracted to an electrode gap (and not electrodes), and is not based at all upon electrorheology.

Note the ability to be attracted to the connection gap is a claim limitation of Applicant's claims, for example, see claim 1 which includes the following:

a mechanism for applying an electric field across said connection gap, said mechanism electrically connected to said at least one pre-synaptic electrode and said at least one post-synaptic electrode, whereby said electric field induces a dipole in each nanoconductor among said plurality of nanoconductors only when said plurality of nanoconductors is located within said liquid dielectric solution, thereby aligning said plurality of nanoconductors within said liquid dielectric solution and attracting said plurality of nanoconductors to said connection gap in order to provide to neural network nanoconnections of a connection network between said at least one pre-synaptic electrode and said at least one post-synaptic electrode within said liquid dielectric solution, said connection network, said liquid dielectric solution, said plurality of nanoconductors, said at least one pre-synaptic electrode and said at least one post-synaptic electrodes electromechanically operable in combination with one another to comprise said electromechanical-based liquid state machine, which stores via patterns of neural activations of said neural network nanoconnections, a recent past history of said electromechanical-based liquid state machine.

The Examiner argued that the evidence shown in the cited papers demonstrates that the concept disclosed by the applicant and cited below will not function as a neural network. The Applicant submits that this is incorrect as the Hong reference demonstrates that nanoconnections can be formed in dielectric solutions. The connections of the Hong reference could modified for use in forming a neural network, which is a discovery first realized by the Applicant. Hong does not of course teach a neural network. Applicant's innovation is the ability to form nanoconnections in a dielectric solution and then using such components as a basis for forming a neural network.

Based on the foregoing, the Applicant submits that the Adriani et al. and Jordan et al. references are not anticipated equivalents of Applicant's electromechanical-based liquid state machine Applicant's invention is not based on the use of "chains". The Examiner has not conclusively established that the invention of the Applicant will simply not function as a neural network, simply because the references cited by the Examiner either do not anticipate Applicant's invention or are irrelevant.
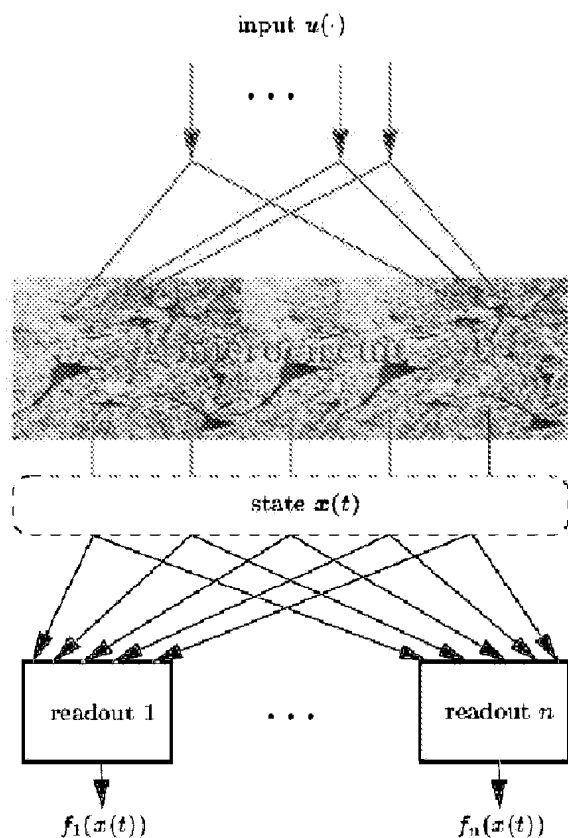
The Applicant also note that none of the references provide for any teaching whatsoever of a liquid state machine. What exactly is a "liquid state machine" (LSM)? The conceptual framework of an LSM facilitates the analysis of the real-time computing capability of neural microcircuit models. It does not require a task-dependent construction of a neural circuit, and hence can be used to analyze computations on quite arbitrarily "found" or constructed neural microcircuit models. An LSM also does not require any a-priori decision regarding the "neural code" by which information is represented within the circuit. A good summary of what an LSM is can be found at the following web site:

http://en.wikipedia.org/wiki/Liquid State Machine

In citing Mehrotra, Jordan, Adriani, and Merkle, the Examiner was silent on the issue of the LSM. None of these references, either individually or in combination with one another, teach an LSM. Of course, it must be appreciated

that the LSM <u>to date</u> has been <u>entirely</u> a <u>computational</u> model, unlike Applicant's invention, which is a <u>physical</u> device. There has <u>not</u> been an actual physical hardware and nanotechnology based liquid state machine developed to date. The basic idea of an LSM as an LSM is known by those skilled in the art is that a neural (recurrent) microcircuit may serve as an unbiased analog (fading) memory (informally referred to as "liquid'" but of course not really a "liquid") about current and preceding inputs to the circuit. The "liquid state" refers to the <u>analogy</u> of a liquid but is <u>not</u> of course in and of itself a liquid. The word <u>liquid</u> in the name of the LSM comes from the <u>analogy</u> drawn to dropping a stone into a still body of water or other liquid. The falling stone will generate <u>ripples</u> in the liquid. The input (motion of the falling stone) has been converted into a spatio-temporal pattern of liquid displacement (ripples).

We refer to the vector of contributions of all the neurons in the microcircuit to the membrane potential at time t of a generic readout neuron as the liquid state x(t). Note that this is all the information about the state of a microcircuit to which a readout neuron has access. In contrast to the finite state of a finite state machine the liquid state of an LSM need not be engineered for a particular task. It is assumed to vary continuously over time and to be sufficient sensitive and high-dimensional that it contains all information that may be needed for specific tasks. The liquid state x(t) of a neural microcircuit can be transformed at any time t by a readout map f into some target output f(x(t)) (which is in general given with a specific representation or neural code). An illustrated example of a liquid state machine is provided in the figure below:

The Liquid State Machine (LSM). The recurrent microcircuit (liquid) transforms the input into states x(t), which are mapped by t he memory-less readout functions f_1, ..., f_n to the outputs $f_1(x(t))$, ..., $f_n(x(t))$.

The liquid state machine is based on the concept that only the synapses of these readout neurons have to be adapted for a particular computational task. This requires that any two different input time series u(s), s $\leq$ t and v(s), s $\leq$ t which should produce different outputs at some subsequent time t put the recurrent circuit into two (significantly) different states $x_u(t)$ and $x_v(t)$ at time t. In other words: the current state x(t) of the microcircuit at time t has to hold all information about preceding inputs.

If the metaphorical "liquid" has this property it is possible to train a memory-less readout to produce the desired output at time t. If one lets t vary, one can use the same principles to produce as output a desired time series or function of time t

with the same readout unit. This yields the following (offline) procedure for training a readout to perform a given task based on the ideas sketched above.

1. Define the neural microcircuit to be analyzed

2. Record states x(t) of the microcircuit at various time points in response to numerous different (training) inputs u(×)

3. Apply a supervised learning algorithm to a set of training examples of the form [x(t),y(t)] to train a readout function f such that the actual outputs f(x(t)) are as close as possible to the target outputs y(t).

One advantage of this approach is that it is not necessary to take any temporal aspects into account for the learning task, since all temporal processing is done implicitly in the recurrent circuit. Furthermore no a-priori decision is required regarding the neural code by which information about preceding inputs is encoded in the current liquid state of the circuit. Note also that one can easily implement several computations in parallel using the same recurrent circuit. One just has to train for each target output a separate readout neuron, which may all use the same recurrent circuit.

The foregoing description of a "liquid sate machine" is simply not taught or disclosed or anticipated by the references cited by the Examiner herein. The Applicant's specification, on the other hand, at paragraph [0028] indicates the following:

Another type of neural network, which has been proposed, is known as a liquid state machine (LMS). A non-limiting and non-essential example of an LMS is disclosed in "Computational Models for Generic Cortical Microcircuits" by Wolfgang Maass, et al., Institute for Theoretical Computer Science, Technische Universitaet Graz, Graz, Austria, June 10, 1003. Note that the aforementioned Maass et al reference is referred to herein for general edification and background purposes only. It is believed that liquid state machines have not been implemented in the context of physical neural networks configured based on nanotechnology. A need thus exists for such devices, including methods and systems thereof.

The Applicant refers to this section of Applicant's specification in order to make two points. First, a liquid state machine is a very particular type of neural network. Second, this type of neural network has only been implemented to date in the context of software simulations such as that disclosed in the Wolfgang Maass reference mentioned above, and not in an actual physical neural network, that is, of course, until the conception of Applicant's invention. Applicant goes on to describe the workings of Applicant's liquid state machine in paragraphs [00328] and [00329] of Applicant's specification as follows:

FIG. 39 illustrates a system 3900 of interconnected neural circuitry referred to in the art as a Liquid State Machine, which can be adapted for use in accordance with an alternative embodiment of the present invention. Physical neural network 3900 thus comprises a Knowm™ enabled liquid state machine. System 3900 generally describes a neural network learning mechanism which can be applied to a physical neural network formed utilizing nanotechnology, as described herein. Such a network generally consists of two or more distinct neural modules. Inputs are presented to the first module, referred to as a Liquid State Machine or LSM. The LSM is generally a randomly connected network of neural circuits. Although the connections may be random, this is not always the case. Generally, the exact nature of the connections are not as important as the statistics of the connection, such as the amount of interconnectivity. However such a LSM is connected, its sole purpose is to provide what is referred to in the art as an "analog fading memory". In a liquid state machine, memory tends to fade, similar to the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof.

The LSM can store, via patterns of neural activations, its recent past history. Other types of neural circuits can be utilized to extract the "state" of the LSM. A state -extracting neural circuit can be accomplished by a very simple learning neuron, such as, for example, a perceptron. Such perceptrons can adjust their synaptic weights so as to produce a desired output. Such perceptrons can be referred to as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between the neural circuits within the LSM and the read-out neuron output.

Based on the foregoing and a thorough reading of Applicant's specification it can be appreciated that a liquid state machine or LSM of Applicant's invention, in order to function, includes the use of read-out neurons, a linear mapping between neural circuits and perceptrons that can adjust their synaptic weights to as to produce a desired output. Additionally, in an LSM memory tends to fade, similar to

the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof. This does not mean of course that "water" is an element of a liquid state machine. The reference to "liquid" in the name "liquid state machine" is only a metaphor for how the device functions. That is, the word liquid in the name comes from the analogy drawn to dropping a stone into a still body of water or other liquid. The falling stone will generate ripples in the liquid. The input (motion of the falling stone) has been converted into a spatio-temporal pattern of liquid displacement (ripples).

Applicant believes that the previous attempts by the Examiners to compare the liquid dielectric of the Applicant's invention to the "liquid" of the liquid-state machine is a result of a lack of understanding of what a "liquid state machine" is. An LSM can be thought of as a decaying dynamic memory. In this way, it is not waves of a liquid that are decaying. It is neural signals in feedback loops within a neural network. In the system described by Applicant's invention, the dynamic decaying memory are the electrical signals being passed between neural circuits through the Applicant's synaptic device element. The references cited by the Examiner, on the other hand, do not teach or disclose this, but describes only a simple logic circuit and electrolytic memory element, which bares no similarity to the synaptic device element described by the Applicant.

A liquid state machine in the past has been presented by various researchers and software scientists as a computational construct and includes a large collection of units (called *nodes*, or *neurons*). Each node receives time varying input from external sources (the inputs) as well as other nodes. Nodes are randomly connected to each other. The recurrent nature of the connections turns the time varying input into a spatio-temporal pattern of activations in the network nodes. The spatio-temporal patterns of activation are read out by linear discriminant units. The soup of recurrently connected nodes will end up computing a large variety of nonlinear functions on the input. It is important to keep in mind, however, that

such components and functions of a liquid state machine have only been presented in the context of neural network software simulations. Applicant believes that prior to Applicant's invention there has not been any prior art, which teaches, suggests or discloses an actual physical neural network (not software) that is an LSM.

Given this description of a liquid state machine, which is taught by Applicant's invention, it is difficult to identify the workings of a liquid state machine in the references cited by the Examiner. It is also difficult to see how such references teach, disclose or even suggest an LSM.

III.   Claims Rejections 35 U.S.C. § 101

The Examiner rejected claims 21-41 under 35 U.S.C. 101, arguing that the claimed invention lacks patentable utility. The Examiner argued that the neural network that is claimed cannot develop and the whatever network that may develop, cannot function as a neural network because it is not a neural network ... chains are not neural networks. The Applicant respectfully disagrees with this assessment. Applicant does not use "chains" and the Hong reference demonstrates connections that could be adapted for use in a neural network by applying Applicant's claimed invention. Applicant's invention does provide patentable utility...what is more "utilitarian" than a nanometer-scale physical neural network? Applicant's specification indicates that the physical neural network of Applicant's invention would be much faster than any present software-based neural network solutions. Regarding utility, Applicant's specification provides many examples of utility. FIGS. 14-18 of Applicant's specification, for example, describe a chip-implementation of Applicant's invention. This constitutes one example a practical application for practicing Applicant's invention, particularly in light of the features demonstrated by the Hong reference.

Based on the foregoing, Applicant respectfully requests that the rejections under 35 U.S.C. 101 be withdrawn.

IV.   Claims Rejections 35 U.S.C. § 112

The Examiner rejected Claims 21-41 under 35 USC 112, first paragraph by arguing that current case law (and accordingly, the MPEP) require such a rejection if a 101 rejection is given because when Applicant has not in fact disclosed the practical application for the invention, as a matter of law there is no way Applicant could have disclosed how to practice the undisclosed practical application.

The Applicant respectfully disagrees with this assessment.   As indicated previously, Applicant does not use "chains" and the Hong reference demonstrates connections that could be adapted for use in a neural network by applying Applicant's claimed invention.   Applicant's invention does provide patentable utility...what is more "utilitarian" than a nanometer-scale physical neural network? Applicant's specification indicates that the physical neural network of Applicant's invention would be much faster than any present software-based neural network solutions.   Regarding utility, Applicant's specification provides many examples of utility.   FIGS. 14-18 of Applicant's specification, for example, describe a chip-implementation of Applicant's invention.   This constitutes one example a practical application for practicing Applicant's invention, particularly in light of the features demonstrated by the Hong reference.

Based on the foregoing, Applicant respectfully requests that the rejections under 35 U.S.C. 112 be withdrawn.

V.   Claims Rejections, 35 U.S.C. § 102 / § 103

The Examiner argued that claims 21-41 fail to identify an invention (neural network) that can be evaluated under the conditions of novelty or nonobviousness. The Examiner argued that the approach taken using nanoconductors fails to produce a neural network. The Examiner also asserted that the claims as written have no basis in reality and cannot be evaluated because the invention doesn't and cannot exist. The Examiner further argued that if the Applicant is not claiming a neural network, then the chains of Adriani and the dipoles of Jordan anticipate the

applicant's invention. The Applicant respectfully disagrees with this assessment. Applicant has identified an invention that can be evaluated under the conditions of novelty or nonobviousness. The approach taken by Applicant can provide for a neural network. Applicant's specification and the Hong reference provide sufficient evidence to make this point. Applicant's invention does have a basis in reality (i.e., see Hong reference for forming connections in a gap). Additionally, as indicated previously, neither Adrianai nor Jordan anticipate Applicant's invention and further, Applicant's invention does not form chains nor utilize such "chains".

VI. Conclusion

The Applicant has clarified the structural distinctions of the present invention via the amendments submitted herewith. Such amendments are enabled and support by Applicant's specification and do not constitute new matter. Reconsideration and allowance of Applicant's application is therefore respectfully solicited.

Should there be any outstanding matters that need to be resolved, the Examiner is respectfully requested to contact the undersigned representative to conduct a telephonic interview with the Applicant (Alex Nugent) in an effort to expedite prosecution in connection with the present application.

Respectfully submitted,

Dated: July 25, 2007

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